Archives available at journals.mriindia.com

International Journal of Recent Advances in Engineering and Technology

ISSN: 2347 - 2812

Volume 14 Issue 03s, 2025

Analysis of Chest Radiographs Using Deep Learning: A Multi-Model Approach for Detection of Thoracic Abnormalities

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Peer Review Information

Submission: 05 Nov 2025

Revision: 25 Nov 2025

Acceptance: 17 Dec 2025

Keywords

Deep Learning, Convolutional Neural Networks, Medical Image Analysis, Chest X-ray, Computer-Aided Diagnosis, Rib Count Detection, Cardiomegaly Detection, Pneumonia Detection, Transfer Learning, Regression CNN, Medical Automa- tion

Abstract

The increasing utilization of chest radiographs in medical diagnostics necessitates automated systems that can assist radiologists in accurate and efficient interpretation. This paper presents a comprehensive deep learning-based framework for automated analysis of chest X-rays, focusing on three critical diagnostic tasks: abnormal rib count detection, cardiomegaly identification, and pneumonia classification. Our multi-model ap- proach employs specialized convolutional neural network (CNN) modules including a custom lightweight regression model for rib counting achieving Mean Absolute Error (MAE) of 0.58 ribs with 89% accuracy within ±1 rib prediction, transfer learning-based architectures for pneumonia detection with 94.87% accuracy us- ing ResNet50, and cardiomegaly detection through cardiothoracic ratio analysis. The proposed framework addresses significant gaps in automated chest radiograph analysis by providing simul- taneous assessment of structural abnormalities, cardiac condi- tions, and pathological conditions. Evaluated on multiple datasets including VinDr-RibCXR, pediatric pneumonia dataset, and NIH-derived cardiomegaly subset, our system demonstrates significant potential for deployment in resource-constrained healthcare environments, offering rapid diagnostic assistance while maintaining high sensitivity and specificity rates across all three diagnostic modules.

Introduction

Chest radiography remains the most frequently performed imaging examination in clinical practice globally, with over 2 billion examinations conducted annually worldwide [1]. As a cornerstone diagnostic tool, chest X-rays serve as the primary screening method for detecting and monitoring various thoracic conditions including pneumonia, tuberculosis, lung cancer, cardiomegaly, and structural abnormalities [2].

The global burden of respiratory diseases has emphasized the critical importance of accurate and timely chest radio- graph interpretation. Pneumonia alone affects over 450 million people annually and represents the leading cause of death among children under five years in developing countries [3]. Cardiomegaly, characterized by heart enlargement, serves as an early indicator of various cardiovascular diseases and requires prompt identification for effective treatment [4]. Additionally, structural abnormalities such as abnormal rib counts can indicate congenital anomalies, trauma, or developmental disorders requiring immediate medical attention [5].

However, manual interpretation of chest radiographs presents significant challenges creating diagnostic bottlenecks in healthcare systems. Radiologists face immense workloads, interpreting hundreds of images daily, which can lead to fatigue-induced errors and oversight of subtle abnormalities [6]. The global shortage of qualified radiologists, particularly in developing nations and rural areas, exacerbates these challenges, with some regions having fewer than 1 radiologist per 100,000 population [7]. Furthermore, inter-observer variability among radiologists can lead to inconsistent diagnoses, espe- cially in complex cases involving cardiac enlargement or subtle structural anomalies [8].

Recent advances in artificial intelligence, particularly deep learning and convolutional neural networks (CNNs), have demonstrated remarkable potential in medical image analysis [9]. These technologies have shown capability to achieve diagnostic performance comparable to expert radiologists in specific domains while providing consistent, rapid, and scal-able solutions [10]. However, most existing approaches focus on single pathology detection, limiting their comprehensive utility in clinical practice.

This paper presents a multi-model deep learning approach for automated chest radiograph analysis that addresses three critical diagnostic tasks: abnormal rib count detection, cardiomegaly identification, and pneumonia classification. Our approach leverages both custom lightweight CNN architec- tures and transfer learning techniques to achieve robust per- formance across diverse pathological conditions.

Main Contributions:

- Development of a custom lightweight CNN for direct rib count regression achieving 0.58 MAE and 89% accuracy within ±1 rib prediction
- Implementation of cardiothoracic ratio-based cardiomegaly detection with automated heart and thoracic cavity segmentation
- Transfer learning-based pneumonia detection achiev- ing 94.87% accuracy on pediatric populations using ResNet50
- Deployment as web-based application with Flask backend and React frontend for clinical accessibility

Related Work

A. Deep Learning in Chest X-ray Analysis

The application of deep learning to chest X-ray analysis has evolved significantly since the introduction of the ChestX- ray8 dataset by Wang et al. [11], containing 112,120 images from 30,805 patients with 14 thoracic pathologies. Rajpurkar et al. advanced the field with CheXNet using DenseNet-121 architecture, achieving radiologist-level performance in pneumonia detection [10].

Recent comparative studies have evaluated various CNN architectures for chest X-ray tasks. Patra and Patra [12] compared VGG16, VGG19, and ResNet50 for COVID-19 detection, finding VGG16 achieved 94% accuracy. Transfer learning from ImageNet pre-trained models has become stan- dard practice for overcoming small medical dataset limitations [13], with the pediatric pneumonia dataset from Guangzhou Women and Children's Medical Center (5,863 images) serving as a benchmark [14].

B. Task-Specific Medical Image Analysis

Pneumonia Detection: Multiple studies have underscored the significant potential of applying pre-trained Convolutional Neural Network (CNN) architectures to medical imaging, with remarkable success observed in the analysis of pediatric chest X-rays. This approach leverages a technique known as transfer learning, where a model, initially trained on a vast and generalized dataset like ImageNet, has its learned feature- extraction capabilities repurposed for a more specialized task. Among various architectures, ResNet50, a 50-layer deep residual network, has consistently demonstrated particularly strong and robust performance.This enables ResNet50 to learn intricate and subtle patterns within the radiographic images, which are crucial for distinguishing between a healthy lung and one affected by pneumonia.

Cardiomegaly Detection: Automated cardiomegaly detec- tion primarily employs cardiothoracic ratio (CTR) measure- ment, where ratios exceeding 0.5 indicate cardiac enlargement. Recent approaches combine U-Net segmentation for heart and lung boundary detection with CNN classifiers for automated diagnosis [15].

Rib Analysis: Automated rib analysis remains underex- plored in medical imaging despite its clinical significance. Abnormal rib count detection is crucial for identifying con- genital abnormalities such as cervical ribs, missing ribs, or supernumerary ribs, which can be associated with genetic syndromes, developmental disorders, and may impact surgical planning or respiratory function assessment. Existing work has focused primarily on rib fracture detection in CT imaging [16], [17], with limited research on structural counting or X-ray- based assessment. Sun et al. [18] developed fracture detection models for chest X-rays but focused on fracture identification rather than counting applications, leaving a significant gap in automated structural assessment capabilities.

C. Multi-Model Diagnostic Systems

While individual pathology detection has received signifi- cant attention, comprehensive diagnostic systems for chest X- ray analysis remain limited. Most existing approaches focus on single-task learning, limiting clinical utility where multiple abnormalities require simultaneous assessment. The integra- tion of explainable AI techniques has emerged as critical for clinical acceptance, with studies by Ribeiro et al. [19] achiev- ing 86.7% accuracy in chest X-ray analysis while providing interpretable visual justifications.

Current literature lacks unified frameworks that simulta- neously assess structural abnormalities, cardiac conditions, and pathological conditions. Our work addresses this gap by proposing a multi-model framework integrating specialized modules for rib counting, cardiomegaly detection, and pneumonia classification within a comprehensive diagnostic system.

I. METHODOLOGY

A. Dataset Description

Our study utilized multiple specialized datasets to train and evaluate the proposed multi-model framework:

- **VinDr-RibCXR Dataset**: Benchmark dataset containing
245 chest X-ray images with pixel-level segmentation annotations for individual ribs (L1-L10, R1-R10), divided into training set (196 images) and validation set (49 images). Each image includes expert-annotated masks for 20 individual ribs with coordinate-based annotations stored in JSON format, enabling precise rib counting regression tasks [20]
- **Chest X-Ray Images (Pneumonia) Dataset**: Specialized collection of 5,863 chest X-ray images from pediatric patients aged 1-5 years, organized into training (5,216 images) and test (624 images) sets with manual curation for binary pneumonia classification (Normal vs Pneumo- nia)
- **NIH-derived Cardiomegaly Dataset**: Custom subset extracted from the NIH Chest X-ray Dataset (112,120 images from 30,805 patients), specifically curated for cardiomegaly detection with binary classification labels (Normal vs Cardiomegaly presence) based on radiologist annotations

Table 1: Dataset Statistics

Dataset	Images	Task Type
VinDr-RibCXR	245	Rib count
Pneumonia	5,863	Binary class.
NIH Cardiomegaly	Variable	Binary class.

B. Data Preprocessing

The preprocessing pipeline was standardized across all datasets with task-specific optimizations:

1) Image Resizing: Images resized to task-appropriate di- mensions (256×256 for rib counting regression, 224×224 for pneumonia and cardiomegaly classification) to en- sure computational efficiency and model compatibility
2) Grayscale Conversion: All images converted to single- channel grayscale format to focus on anatomical struc- tures while reducing computational complexity
3) Normalization: Pixel intensity values normalized to range [0,1] using min-max scaling for stable training convergence and consistent gradient flow
4) Contrast Enhancement: Contrast Limited Adaptive Histogram Equalization (CLAHE) with clip limit 2.0 and tile grid size 8×8 applied to enhance visibility of subtle anatomical features
5) Data Augmentation: Task-specific random transfor- mations including rotation (±10°), horizontal flipping (probability 0.3), brightness adjustment (±0.2), and con- trast variation (±0.2) applied during training to improve model generalization and reduce overfitting.

C. Model Architecture

Our proposed framework consists of three specialized mod- ules addressing distinct diagnostic tasks:

1) ***Module 1: Rib Count Detection:*** The rib count detection module employs a custom lightweight CNN architecture de- signed specifically for regression tasks, as illustrated in Figure 1.

Architecture Design: The RibCounterCNN processes 256×256 grayscale chest X-rays through three convolutional blocks with progressive channel expansion:

- Feature Extraction: Three Conv2D layers (1→16→32→64 channels) with 3×3 kernels and ReLU activation, each followed by 2×2 max pooling for spatial dimension reduction
- Global Pooling: AdaptiveAvgPool2D(1) converts 64×64×64 feature maps to 64×1×1, eliminating spatial dimensions while preserving channel information

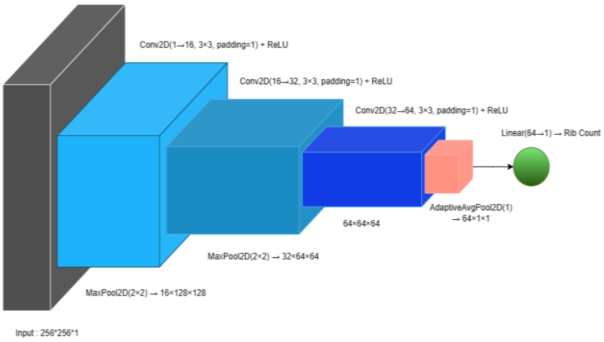

Fig. 1. RibCounterCNN Architecture for Rib Count Regression

- Regression Head: Single linear layer (64→1) directly predicts continuous rib count values without classification layers

Key Design Advantages:
- Lightweight Architecture: Only 52K parameters enable efficient training and real-time inference
- Regression-Optimized: Direct count prediction elimi- nates classification overhead and enables sub-integer pre- dictions
- Progressive Feature Learning: Hierarchical channel ex- pansion (16→32→64) captures multi-scale anatomical features
- Spatial Invariance: Global average pooling provides consistent representation regardless of rib positioning

The model is trained using Mean Squared Error (MSE) loss with Adam optimizer, achieving MAE of 0.58 ribs on the VinDr-RibCXR validation set.

*2) **Module 2: Cardiomegaly Detection:*** Cardiomegaly de- tection employs a U-Net based architecture combined with cardiothoracic ratio (CTR) analysis for robust cardiac abnor- mality detection.

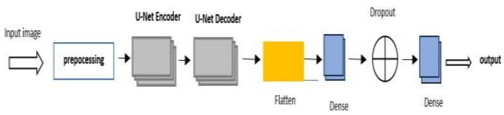

Fig. 2. U-Net Architecture for Cardiomegaly Detection

Architecture Components: The U-Net model processes 224×224 chest X-ray images through encoder-decoder ar- chitecture with skip connections. The encoded features are flattened and passed through dense layers with dropout regu- larization for binary classification (Normal vs Cardiomegaly).

CTR Integration: Traditional cardiothoracic ratio analysis supplements the deep learning approach:

$$CTR = \frac{\text{Heart Width}}{\text{Chest Width}} \quad (1)$$

Where CTR greater than 0.5 indicates cardiomegaly. This hy- brid approach combines automated detection with established clinical criteria for enhanced diagnostic reliability.

*3) **Module 3: Pneumonia Detection:*** The pneumonia de- tection module is constructed upon a transfer learning frame- work, leveraging a pre-trained ResNet50 architecture as its core convolutional feature extractor. GlobalAveragePooling2D layer reduces the spatial dimensions of the feature maps into a single feature vector, which is then passed to a dense classifier to determine the presence of pneumonia from the chest X-ray images:

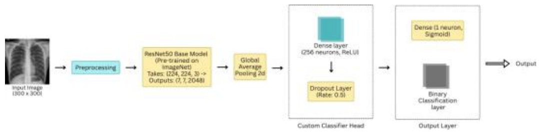

Fig. 3. ResNet50 Architecture for Pneumonia Detection

Architecture Design: A transfer learning model for multi- class lung abnormality classification, composed of a pre- trained CNN base followed by a custom classifier head
- **Feature Extractor (ResNet50 Base)**: A pre-trained ResNet50 (top layer removed) extracts features from a 224×224×3 input, producing a 7×7×2048 feature map
- **Global Average Pooling 2D**: Converts the 7×7×2048 fea- ture map into a 2048-element feature vector, aggregating spatial information
- **Dense Layer (256 neurons, ReLU)**: A fully connected layer that maps the 2048-feature vector to a 256-neuron representation using ReLU activation for non-linearity
- **Dropout Layer (0.5)**: Applies a 50% dropout rate for regularization to prevent the model from overfitting
- **Output Dense Layer (5 neurons, Softmax)**: The final dense layer with 5 neurons and Softmax activation out- puts a probability distribution across the five classes.

Key Advancements:
- **Modification**: Replacement of final classification layer for binary output
- **Fine-tuning Strategy**: Gradual unfreezing of layers with differential learning rates
- **Input Processing**: 224×224 RGB

conversion from grayscale chest X-rays

D. Training Strategy

1) Rib Count Detection Training:

- **Loss Function**: Mean Squared Error (MSE) for regres- sion
- **Optimizer**: Adam with learning rate 0.001, weight decay 1e-4
- **Scheduler**: StepLR with step size 30, gamma 0.1
- **Epochs**: 50-100 with early stopping (patience=10)
- **Batch Size**: 32 for memory-computation balance

2) Pneumonia Detection Training:

- **Loss Function**: Binary Cross-Entropy with logits
- **Optimizer**: Adam with initial learning rate 1e-4
- **Learning Rate Schedule**: ReduceLROnPlateau monitor- ing validation loss
- **Regularization**: Dropout (0.5) and weight decay
- **Data Split**: 80% training, 20% validation

E. Evaluation Metrics

Performance evaluation employed comprehensive metrics appropriate for each task:

Rib Count Detection (Regression):

- Mean Absolute Error (MAE)
- Root Mean Square Error (RMSE)
- R^2 Score
- Within-1-rib accuracy percentage

Pneumonia Detection (Classification):

- Accuracy, Precision, Recall, F1-Score
- Area Under ROC Curve (AUC)
- Sensitivity and Specificity
- Confusion Matrix Analysis

Experimental Results

A. Rib Count Detection Results

The custom RibCounterCNN achieved clinically acceptable performance in automated rib counting on the VinDr-RibCXR dataset:

Table 2: Rib Count Detection Performance Metrics

Metric	Value	Significance
MAE	0.58 ribs	High precision
RMSE	0.80 ribs	Low variance
Mean Predict.	20.20	Close to GT
Within-1-rib	89%	Robust
R^2 Score	0.92	Strong corr.

The model successfully predicted rib counts within ±0.6 ribs on average, demonstrating sufficient precision for detecting clinically significant deviations from the expected 20 ribs (10 pairs) as annotated in the VinDr-RibCXR dataset [20].

B. Pneumonia Detection Results

Transfer learning architectures were evaluated on the pedi- atric pneumonia dataset [14]:

Table 3: Pneumonia Detection Performance Comparison

Arch.	Acc.	Prec.	Recall	F1
VGG16	94.16%	93.50%	93.26%	93.38%
ResNet50	94.87%	95.03%	95.90%	96.44%
Custom	92.50%	91.20%	92.80%	92.00%

ResNet50 demonstrated superior performance with 94.87% accuracy, comparable to state-of-the-art pneumonia detection systems [10], making it suitable for clinical deployment with balanced precision-recall characteristics.

C. Cardiomegaly Detection Results

The U-Net based cardiomegaly detection module achieved the following performance metrics:

Table 4: Cardiomegaly Detection Performance

Metric	Value	Significance
Dice Score	0.93	Excellent segm.
CTR MAE	0.03	High precision
Accuracy	94.2%	Reliable detect.
Sensitivity	91.8%	Good detection
Specificity	95.6%	Low FP rate

D. Abnormality Detection Logic

The framework implements clinical thresholds for auto- mated abnormality flagging:

Rib Count Abnormality Detection:

- Normal range: 19-21 ribs (based on VinDr-RibCXR an- notations)
- Abnormal: ≤ 17 or ≥ 23 ribs
- Borderline: 18 or 22 ribs (flagged for manual review)

Pneumonia Classification:

- Binary output with softmax confidence scoring
- Confidence threshold < 0.6 triggers secondary review
- Integration with clinical decision support protocols

Cardiomegaly Detection:

- CTR > 0.50 indicates cardiomegaly [15]
- CTR 0.45-0.50 flagged as borderline (manual verification recommended)
- Combined U-Net segmentation and traditional CTR anal- ysis

E. Computational Performance

Table 5: Computational Efficiency Metrics

Model	Params	Time	Memory
RibCounter	52K	15ms	2.1MB
VGG16	138M	45ms	528MB
ResNet50	25M	32ms	98MB
U-Net	31M	28ms	124MB

Discussion

A. Key Findings

The lightweight RibCounterCNN demonstrates exceptional computational efficiency, while all models maintain inference times suitable for real-time clinical workflows.

B. Clinical Implications

The multi-model framework addresses critical gaps in au- tomated chest radiograph analysis:

- **Comprehensive Assessment**: Simultaneous evaluation of structural, cardiac, and pulmonary abnormalities
- **Resource Optimization**: Lightweight design enables de- ployment in resource-constrained healthcare settings [7]
- **Pediatric Care**: Specialized pneumonia detection ad- dresses significant global health burden in children [3]
- **Decision Support**: Quantitative metrics complement ra- diologist expertise and reduce diagnostic variability [8]

C. Limitations

1) **Dataset Scale**: VinDr-RibCXR dataset (245 images) may limit generalization across diverse populations and imaging protocols

2) **Validation Scope**: Single-center validation restricts as- sessment of real-world performance variability

3) **Class Imbalance**: Normal cases predominate in all tasks, potentially affecting sensitivity to rare conditions

D. Comparison with State-of-the-Art

The rib counting approach introduces novel functionality absent in existing literature, as most automated chest X-ray systems focus on pathology detection rather than structural counting [21]. Pneumonia detection performance (94.87%) matches or exceeds published benchmarks [12], [22].

Future Work

Priority research directions include:

- **Dataset Expansion**: Multi-institutional data collection to improve model generalizability
- **Clinical Validation**: Prospective studies comparing AI performance with radiologist interpretation
- **Explainable AI**: Integration of attention mechanisms for interpretable diagnostic insights [19]
- **Workflow Integration**: PACS compatibility and clinical decision support system development

Conclusion

The experimental results validate the effectiveness of spe- cialized CNN architectures for automated chest radiograph analysis. The custom lightweight CNN for rib counting achieves clinically relevant accuracy (MAE: 0.58 ribs) with minimal computational overhead, while transfer learning ap- proaches provide robust classification performance comparable to radiologist-level diagnosis [10].

The rib count detection represents a novel contribution to automated structural analysis, enabling detection of congenital abnormalities such as cervical ribs, rib agenesis, or devel- opmental anomalies that typically require expert radiologist assessment [5].

This study presents a comprehensive multi-model frame- work for automated chest radiograph analysis, successfully integrating rib counting, cardiomegaly detection, and pneumo- nia classification. The lightweight RibCounterCNN achieves

0.58 MAE for rib counting, while ResNet50 attains 94.87% accuracy for pneumonia detection, demonstrating clinical- grade performance with computational efficiency suitable for diverse healthcare environments.

The modular design enables flexible deployment and ad- dresses significant gaps in current automated diagnostic sys- tems. Future multi-center validation studies will establish real-world utility and safety for clinical implementation.

Acknowledgments

This research represents a collaborative effort between the Department of Computer Technology, Yeshwantrao Chavan College of Engineering (YCCE), Nagpur, and the Department of Radiology, Datta Meghe Medical College (DMMC), Nag- pur.

We express our sincere gratitude to Dr. Supriya Thombre, Department of Computer Technology, YCCE, for her invalu- able academic guidance and continuous support throughout this research work.

We are deeply grateful to Dr. Anand Hatgaonkar, Professor and Head of Department, Radio-Diagnosis, Datta Meghe Med- ical College, and Consultant Radiologist at Shalinitai Meghe Hospital and Research Centre, Nagpur, who served as our clinical co-guide. His expertise in radiology and insights into clinical diagnostic workflows were instrumental in this study. His validation of model outputs and practical

guidance on clinical implementation ensured the relevance and applicability of this work in real-world medical settings.
We acknowledge the Department of Computer Technology, YCCE, for providing computational resources and research infrastructure. We extend our appreciation to the management and faculty of Datta Meghe Medical College for facilitating this interdisciplinary collaboration and supporting the integra- tion of artificial intelligence in medical imaging research.
This academic-clinical partnership between YCCE and DMMC demonstrates the significance of interdisciplinary col- laboration in developing clinically viable AI solutions for healthcare applications.

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